

Evaluating the Effects of Digitalization on Workforce Demand in Manufacturing Industries.

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Abstract

Manufacturing Industries in China exhibited an anticipated trend from 2010 to 2022: the rollout of digital transformation resulted in a significant increase in general employment. Our analysis learns of a growth trend and a shift in capabilities across listed firms. The number of highly skilled and moderately to highly skilled workforce rose, whereas the number of low- and moderately skilled roles plummeted. In particular, digitalization has facilitated employment opportunities in financial accounting, product sales, and research and development (R&D). The increase in size results from the advantages gained from producing on more acres and improving efficiency. Remarkably, substituting a low-skilled workforce with digital technology did not impede employment.

Moreover, due to robust governance, competitive industries, and less favorable marketplaces, enterprises were driven to enhance their workforce through digitalization. These findings provide insight into the intricate relationship between digitalization and workforce employment in China's manufacturing sector.

Keywords: Digital Transformation, Workforce Employment, Manufacturing Industries, Managerial efficiency, Labor Market Dynamics

ملخص

شهدت الصناعات التحويلية في الصين اتجاهًا متوقعًا خلال الفترة من 2010 إلى 2022، حيث أدى تطبيق التحول الرقمي إلى زيادة ملحوظة في التوظيف العام. ويُشير تحليلنا إلى وجود اتجاه نمو وتحول في القدرات لدى الشركات المدرجة. فقد ارتفع عدد القوى العاملة ذات المهارات العالية والمتوسطة إلى العالية، بينما انخفض عدد الوظائف ذات المهارات المنخفضة والمتوسطة بشكل حاد. وعلى وجه الخصوص، سهّلت الرقمنة فرص العمل في مجالات المحاسبة المالية، ومبيعات المنتجات، والبحث والتطوير. ويعود هذا النمو في حجم العمل إلى المزايا المكتسبة من الإنتاج على مساحات أكبر وتحسين الكفاءة. ومن اللافت للنظر أن استبدال القوى العاملة ذات المهارات المنخفضة بالتكنولوجيا الرقمية لم يؤثر سلباً على التوظيف.

علاوة على ذلك، ونظراً للحكومة الرشيدة، والمنافسة الشديدة في القطاعات الصناعية، وظروف السوق غير المواتية، فقد سعت الشركات إلى تعزيز كوادرها العاملة من خلال الرقمنة. وتُقدم هذه النتائج رؤى ثاقبة حول العلاقة المعقدة بين الرقمنة وتوظيف القوى العاملة في قطاع الصناعات التحويلية في الصين.

الكلمات المفتاحية: التحول الرقمي، توظيف القوى العاملة، الصناعات التحويلية، الكفاءة الإدارية، ديناميكيات سوق العمل

1. Introduction

China, a manufacturing powerhouse, is central to digital transformation (Chen et al. 2024). The proliferation of artificial intelligence, extensive data stores, and the Internet of Things drives this transformation, which has both beneficial and adverse effects, particularly for the labor force in China's manufacturing sectors (Paschen et al. 2021) and (Dapeng Yu Bintong Ma 2023).

China's digital market experienced remarkable growth, reaching a value of 6.9 trillion USD (or 51.1 trillion yuan) in 2022, positioning it as the second largest globally (Nikitaeva, Serdyukov, and Fedosova 2021). This surge stimulated economic growth, fostering technological advancements and creating new prospects for firms (Brenner and Hartl 2021) and (Yunxia, Neng, and Yechi 2023). The China Academy of Information and Communications Technology (CAICT) expects a significant association between the digital market and job opportunities, with an estimated 401 million jobs added by 2025 (B. Wu and Yang 2022).

However, digitalization's impact on the workforce's makeup is intricate. Numerous studies suggest that the emergence of new industries and enterprises would lead to a growth in job prospects (Ciarli et al. 2021) and (Nambisan 2017)]. However, there are concerns that robots may replace human employees, particularly in China's manufacturing sector, which largely depends on the workforce (Dapeng Yu Bintong Ma 2023) and (Rani and Furrer 2021). This research explores the intricate relationship between digitalization and workforce dynamics in Chinese manufacturing organizations, going beyond the simplistic decision between job creation and transfer. In order to unravel this complexity, crucial inquiries aim to address:

Will digital transformation result in Chinese manufacturing firms increasing their employment, reducing their workforce, or restructuring their workforces?

How does digitalization's impact vary between industries that need significant capital investment and those that rely heavily on labor, as well as between government hands and privately held firms?

Total factor production refers to the overall output or productivity generated by using all available inputs or factors of production in an economic system. Digital transformation has the potential to create a more skill-intensive workplace by enhancing performance via the optimization of procedures and resource utilization (Y. Wu et al. 2023). This might result in a higher output level, which would need a corresponding increase in the number of employees. While previous studies have taken a broad approach, this study seeks to provide a more detailed understanding by examining the impact of digitalization on individual Chinese manufacturing firms. An in-depth examination of worker dynamics may be achieved by studying the various effects across different kinds of businesses (Li and Zhao 2023).

The primary objective of this research is to provide valuable information to academics, corporate managers, and lawmakers. Analyzing the intricate relationship between digitalization and worker behavior might provide valuable insights for devising strategies to negotiate the expansion of China's industrial industry (Coskun-Setirek and Tanrikulu 2021). Tomorrow's workforce may include initiatives for upskilling personnel and implementing courses that equip them for the technological advancements of the contemporary day. Additionally, there may be a need to reconsider workforce leadership practices to optimize productivity and efficiency in a digital environment.

2. Literature review

China is at the center of digital transformation and is a global trailblazer in the manufacturing industry. The paper explores the impact of digital transformation on the workforce of manufacturing firms in China.

Chinese firms may use digital sovereignty, enabled by advancements in cloud computing, computational intelligence (robotics), and vast volumes of data, to enhance information analysis and implementation, resulting in significant development (Dapeng Yu, Bintong Ma 2023), (Sun, Liu, and Tansuchat 2023) and (Tang, Huang, and Liu 2021). Introducing robots, machine learning, and other digital advancements may alienate low-skilled workers, particularly in laborious sectors. This eviction might result in extended periods of unemployment. Upgrading existing jobs may lead to streamlined agreements and less secure employment, as referenced in sources (Gregory, Salomons, and Zierahn 2022) and (Autor 2015).

The digital transformation is causing several changes in the workforce. (Kozinets 2002) states that the rise of the digital age is linked to a shift towards online, flexible, and specialist workforce bookings. The proliferation of digital labor marketplaces and the "gig economy" has led to the emergence of new forms of labor. The employment market has transitioned from low-skilled manufacturing workers to highly trained technicians and persons with empathetic qualities (Siyar et al. 2020) and (Wang, Hu, and Zhang 2021). The impact of digitalization on the stratification of skills is a subject of ongoing debate. Research cited in references (Wang, Hu, and Zhang 2021) indicates a rise in higher- and lower-skilled jobs, whereas middle-skilled occupations are declining. This phenomenon is mainly seen in developed countries. Conversely, research in China indicates a potential change toward a more significant number of workers with moderate abilities and a sharp decrease in employees with low skills.

This research examines the impact of digital transformation on labor market dynamics in Chinese manufacturing companies from a corporate management perspective. Let us propose and examine the following hypotheses:

- Hypothesis 1a: The anticipated reduction in employment is closely correlated with the level of digital transformation.

- H1b: For skilled workers to increase directly related to the extent of the digital revolution.

H2a: Digital transformation enhances managerial efficiency, reducing the need to expand the workforce.

- H2b: Enhanced economies of scale lead to increased workforce employment due to the digital revolution.

H2c: Digital transformation improves all elements' efficiency, enhancing workforce employment.

3. Empirical methodology

3.1. The data's foundation and the sample selection process.

The research used data from manufacturing firms registered on the Beijing and Shanghai stock exchanges (A-shares). The data for the years 2010-2022 was obtained from the China Stock Market & Accounting Research Database. The financial data for each company is derived from its filings with regulatory agencies. At the same time, the statistical analysis of digital transformation is based on research findings in information technology. Various data-cleaning approaches were used to assure the reliability and accuracy of the analysis. Firms eliminated from the stock exchange, firms with abnormal performance indicators (such as ST, *ST, PT), or firms with insufficient data were eliminated. Due to the low number of

inaccuracies (about 2%), any remaining observations containing incorrect information were eliminated. Winsorization was used to restrict the number of data values at their distributions' first and ninth percentiles to mitigate outliers. The sample of 1160 A-share listed manufacturing firms was deemed sufficient.

3.2. Designation and clarification of variables

3.2.1 Dependent variable

The primary variable explained, human capital ($\ln HC$), is defined by the natural logarithm of higher-educated workers and represents workforce employment (Workers). We further assess observations' reliability using the logarithmic mean of all workers ($\ln labor$) (B. Wu and Yang 2022). R&D personnel ($\ln rdp$), as well as managerial workforce ($\ln Manager$).

3.3.2 Explanatory variable

The main Independent variable is digital transformation (DT). Our first step was identifying 297 digitalization buzzwords in firms' annual reports, such as artificial intelligence (AI) and the Internet of Things. Next, we used neural networks to examine the occurrence of these phrases in essential reporting parts. Finally, the rate was divided by 100 to calculate a firm's digital transformation level.

3.2.3. Control variables

The scale of a firm is determined by the natural logarithm of its entire assets using the natural logarithm function. Aged is the logarithmic of the total years after the facility using a natural logarithmic function. Sustainability is measured by the ratio of the entire liability compared to all assets, often known as the return on capital (ROC). Profitability is measured by the return on equity (R&E), the ratio of net revenue to investors' equity. Innovative capability is quantified by a logarithm of the sum invested in research and development (R&D). Tobin's Q, a widely used metric, measures the proportional worth of a corporation. It is computed by dividing the marketplace's value by the difference between the amount of assets and the sum of net intangible properties and net impairments.

3.3. Design of the model.

The regression model we have is outlined below:

$$\ln HC_{it} = \alpha_1 + \alpha_2 DT_{it} + \lambda_0 Control_{it} + \varepsilon_{it} \quad (1)$$

In order to examine the impact of digital transformation on workforce employment, we utilize the mediating effects model proposed by Baron and Kenny, as well as Wen et al. [77,78]. We develop a model as follows:

$$MF_{it} = \alpha_3 + \alpha_4 DT_{it} + \lambda_1 Control_{it} + \mu_{it} \quad (2)$$

$$\ln HC_{it} = \alpha_5 + \alpha_6 DT_{it} + \alpha_7 MF_{it} + \lambda_3 Control_{it} + v_{it} \quad (3)$$

The error term is denoted as ε . The coefficients to be evaluated are represented by α and λ . HC_{it} represents the firm workforce job opportunities, DT_{it} indicates Digital Transformation, and $Control_{it}$ represents the control variables. In addition, we employ a panel fixed effects model and account for person, year, manufacturing, and geographic effects. Subsequently, we employ the natural logarithm of firm's sales as a representation of economic activity of scale indication (Sales). According to (Qiu et al. 2022), the

calculation of the total factor efficiency is performed using the A-Caves-Frazer modified OP technique. The logarithm expression for the C-D output function is as follows:

$$\ln \text{Efficiency}_{it} = \beta_0 + \beta_1 \ln \text{Labor}_{it} + \beta_2 \ln \text{Capital}_{it} + \beta_3 \ln \text{MF}_{it} + \varepsilon_{it} \quad (4)$$

4. Experimental analysis and consequences

4.1. Statistical analysis of data that describes the characteristics of a dataset.

Table 1 presents a statistical analysis of the primary variables. The average workforce turnover is 6.429, with a standard deviation of 1.354. The total number of employees exhibits significant variations between organizations, with a mean of 8.528, a min. of 3.496, and a max. of 12.694. The average digital transformation empowerment score for firms is 0.073, ranging from a low value of 0 to a highest of 3.045. This suggests that the level of digitalization among Chinese organizations is relatively low, and there are only minor variations between different firms. Additionally, all other metrics demonstrate the disparity in capabilities among firms.

Table1. Descriptive statistics of variables

Variable	Mean	SD	Min	Max	p50	N
lnHC	6.429	1.354	1.575	10.017	6.237	9678
lnLF	8.528	1.102	3.496	12.694	8.242	9678
LnR&D	3.633	3.118	0.000	10.164	5.040	9678
lnMG	1.900	0.378	0.000	3.297	1.879	9678
Digital Transformation	0.073	0.189	0.000	3.045	0.010	9678
FIRM SIZE	23.310	1.123	21.094	27.016	23.194	9678
Return on Equity	0.073	0.084	-0.451	0.325	0.063	9678
FIRM AGED	2.887	0.420	0.724	4.000	2.971	9678
R&D INVESTMENT	17.860	2.014	0.000	22.974	18.889	9678
FIRM SOLVENCY	0.420	0.189	0.052	0.840	0.409	9678
Capital Intensity Ratio	2.152	1.365	0.220	22.942	1.837	9678
TobinQ	2.163	1.207	0.000	8.704	1.806	9678
M&E	0.178	0.115	0.021	0.630	0.136	9678
FIRM SALES	22.648	1.302	19.687	26.638	22.533	9678
OPACF	9.103	0.630	7.171	12.747	9.0510	9678

4.2. Test for correlation

The results of the correlation test for all variables are presented in Table 2. (VIF) worked to assess the presence of multicollinearity. All VIF values are below 5, indicating the absence of multicollinearity. The correlation test results indicate that all variables exhibit a significant connection with the explanatory variable lnHC. This supports the scientific credibility of subsequent regression findings.

Table 2. Results of correlation test.

Variable	lnHC	DT	SIZES	R&E	AGED	RDI	FS	CIR	Tobin Q
lnHC	1								
DT	1.23	1							
	0.070*								
SIZES	1.83	0.781*	1						
	**	**							
R&E	1.33	-0.015	0.119**	1					
	0.170*	0	*						
AGED	1.33	0.030*	0.301**	-0.030*	1				
	0.189*	**	*	**					
RDI	1.11	0.100*	0.223**	0.050**	0.070**	1			
	0.200*	**	*	*	*				
FS	1.44	-0.006	0.499**	-0.119*	0.333**	0.014	1		
	0.399*	00	*	**	*	9			
CIR	1.13	0.055*	-0.060*	-0.251*	-0.078*	-0.01	-0.180*	1	
	-0.220*	**	**	**	**	58	**		
Tobin Q	1.16	0.060*	-0.290*	0.179**	-0.0170	0.013	-0.300*	0.040*	1
	-0.201*	**	**	*		9	**	**	

Note: * $p < 0.901$, ** $p < 0.05$, and *** $p < 0.001$.

4.3. Evaluation of panel regression using linear models.

By applying the Fisher unit root test approach, unit root tests were conducted on the two types of variables. The outcomes revealed that all the significance levels were below 0.01, showing that our data exhibits stationarity. Subsequently, in order to assess the reliability of our regression model, we performed a Hausman test, resulting in a $\chi^2(8)$ value of 61.83 and a Prob $> \chi^2$ value of 0.0000. These findings indicate that a fixed effects model is recommended. Table 3 displays the regression outcomes utilizing the panel fixed effects model. Column (1) demonstrates that with every incremental improvement in digital Transformation independence, the firm's workforce employed experiences a substantial rise of 0.0949 units ($p < 0.05$). Column (B) indicates that the use of technology has no significant impact on the recruitment of the whole workforce ($p > 0.1$). Column (C) demonstrates that a one-unit rise in digital transformation leads to a significant increase in demands for the R&D workforce by 0.2601 units ($p < 0.001$). Column (D) indicates that there is a substantial positive relationship between the level of digital independence and the demand for management. Specifically, for every unit rise in digital autonomy, the demand for managers

increases by 0.0602 units ($p < 0.02$). Therefore, hypothesis H1a is deemed invalid, but the hypothesis H1b is confirmed.

Table 3. Linear panel regression results.

Variable	(A)	(B)	(C)	(D)
	lnHC	lnLF	lnR&D	lnM&E
DT	0.0952*** (2.980)	-0.0016 (-0.055)	0.2890*** (2.987)	0.0703** (2.489)
SIZE	0.7034*** (41.100)	0.8123*** (56.980)	0.6578*** (19.703)	0.0879*** (8.377)
R&E	-0.2789*** (-3.678)	-0.5432*** (-6.123)	-0.2456 (-1.456)	0.0678 (1.234)
AGED	0.1678*** (2.700)	0.1570*** (3.500)	0.2030 (1.600)	-0.1660*** (-4.606)
R&D INVET.	0.0055** (1.538)	0.0030** (3.418)	0.0556*** (8.456)	0.0020** (2.150)
FS	0.0128 (0.255)	0.0677 (1.333)	-0.0233 (-0.145)	0.0090 (0.235)
FA	-0.0987*** (-13.666)	-0.1234*** (-14.456)	-0.1555*** (-6.123)	-0.0070 (-2.789)
TobinQ	0.0150*** (3.000)	0.0140*** (3.555)	-0.0148 (-1.200)	0.0050 (1.309)
Constant Term	-10.999*** (-23.920)	-9.3002*** (-25.949)	-12.8025*** (-13.610)	0.8275*** (3.909)
Firms Effect	handled	handled	handled	handled
Time Effect	handled	handled	handled	handled
Regional Effect	handled	handled	handled	handled
Businesses Effect	handled	handled	handled	handled
N	9658	9658	9658	9658
R ²	0.9090	0.9568	0.9456	0.7011

Variable	(A)	(B)	(C)	(D)
	lnHC	lnLF	lnR&D	lnM&E
adj. R^2	0.8989	0.9470	0.9355	0.6765

Note: t-statistic values are in parentheses. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

In addition, intuitively, we find that a larger firm size has more as anticipated, more prominent firms own a more significant number of employees. As firms grow, they tend to grow in size. The capital-labor substitution effect negatively influences the relationship between corporate capital intensity and return on net assets, decreasing labor recruitment. Innovative firms have more chances to enhance their capabilities and recruit excellent employees. Ultimately, the positive outlook of the stock market and the increasing worth of businesses facilitate the expansion of employment opportunities for firms.

4.4. Examining robustness

The object of our research is limited to publicly traded corporations, which may result in the exclusion of helpful data from privately held firms. This gives rise to sample selection bias issues, wherein the sample may not accurately represent the total populace. In order to tackle this issue, we utilize the Heckman two-stage method (Pour et al. 2016) a widely used approach for addressing sample selection bias.

The initial phase uses a Probit model selection equation, as in Table 4, column A. This model calculates the probability of a firm being listed by considering pertinent criteria. The inverse Mills ratio (IMR) is a statistic that captures the decision-making bias.

In the next phase, we do a regression analysis to examine the relationship between the infant mortality rate (IMR) and our variable of interest, human capital. A statistical significance coefficient for the infant mortality rate (p -value < 0.05) indicates the existence of sample selection bias. The use of the Heckman two-stage adjustment is justified to produce unbiased estimates.

After making the necessary modifications, we conducted the analysis again using a panel data fixed effects model. The results are presented in Table 4, specifically in column B. The coefficient for digital transformation empowerment is positively and significantly correlated with a value of 0.453532 (p -value < 0.01). This further supports our original discovery that deploying technological innovation enhances the caliber of employees that a firm recruits.

Table 4 depicts the regression findings of the robustness analysis.

Variable	(A)	(B)	(C)	(D)	(E)	(F)
	Heckman method	two-stage	2SLS-IV	Replace core explanatory variables	Eliminate abnormal samples	Identification of causality of "Broadband China" policy
main						
DT	0.9123*** (9.154)	0.4023*** (4.123)	1.7132** (2.145)		0.1009*** (2.603)	0.9056*** (2.689)
Sizes	0.0566**	0.7564***	0.6344***	0.7891***	0.6678***	0.7098***

Variable	(A) Heckman method	(B) two-stage	(C) 2SLS-IV	(D) Replace explanatory variables	(E) core Eliminate abnormal samples	(F) Identification causality "Broadband China" policy	of of
	(2.612)	(39.200)	(15.500)	(40.400)	(31.009)	(40.300)	
R&E	0.2543	-0.1567*	-0.2134**	-0.2678***	-0.3234***	-0.2679***	
	(1.400)	(-1.800)	(-2.534)	(-3.678)	(-4.456)	(-3.675)	
AGED	0.0572*	0.1890***	0.0456	0.1567***	0.1267*	0.1678***	
	(1.786)	(3.200)	(0.564)	(2.956)	(1.734)	(2.987)	
RD&I	0.0088**	0.0045***	0.0056**	0.0060***	0.0086***	0.0053**	
	(2.456)	(3.987)	(2.456)	(2.745)	(3.789)	(2.675)	
FS	-0.5812***	-0.2627**	-0.0795	0.0230	0.0339	0.0181	
	(-5.602)	(-2.700)	(-1.066)	(0.248)	(0.257)	(0.158)	
FA	0.1185***	-0.0498*	-0.0939***	-0.0871***	-0.0691***	-0.0781***	
	(11.106)	(-1.799)	(-10.875)	(-12.897)	(-8.082)	(-11.908)	
TobinQ	0.0560***	0.0420***	0.0129*	0.0155***	0.0110**	0.0171***	
	(4.390)	(4.220)	(1.892)	(2.780)	(2.199)	(2.999)	
imr		0.8266***					
		(2.912)					
Digital				0.0431***			
				(4.984)			
TreatPost						0.0671***	
						(3.458)	
Constant Term	-1.5637***	-10.6759***		-10.7893***	-8.7789***	-9.5299***	
	(-4.270)	(-22.199)		(-26.933)	(-29.739)	(-26.914)	
Firm Effect		handled	handled	handled	handled	handled	
Time Effect		handled	handled	handled	handled	handled	

Variable	(A) Heckman method	(B) two-stage	(C) 2SLS-IV	(D) Replace core explanatory variables	(E) Eliminate abnormal samples	(F) Identification of causality of "Broadband China" policy
Regional Effect		handled	handled	handled	handled	handled
Industry Effect		handled	handled	handled	handled	handled
<i>N</i>	9478	9658	9658	9658	9658	9658
<i>R</i> ²		0.9260	0.0904	0.9233	0.9100	0.9234
adj. <i>R</i> ²		0.9140	−0.0705	0.9141	0.9082	0.9189

Our approach recognizes the possibility of a reciprocal relationship between digital Transformation and workforce employment. The Durbin-Wu-Hausman (DWH) test provides evidence supporting this hypothesis ($\chi^2_1(1) = 7.068$, $p = 0.0097 < 0.0041$). In order to tackle this problem of endogeneity, we utilize an instrumental variable (IV) strategy.

In the study by (Smith, Smith, and Shaw 2017), we regard the number of web surfers and city cellphone users as possible instrumental factors for digital Transformation.

The 2SLS-IV approach produces an F-statistic of 210.19, LM statistic of 41.499, and a $\chi^2_1(1)$ p-value of 0.0001, all of which indicate satisfactory under-identification assessment.

The Wald F-statistic (29.595) surpasses the Stock-Yogo weakly instrumental variable test threshold (15.93) at the 10% significance level, indicating a successful passage of the weaker instrumental variable test.

The computed coefficient of digital independence is considerably positive (1.7488, $p < 0.05$).

The results indicate a solid and favorable impact of Digital Transformation on recruiting employees in the firm workforce.

Columns (D): We utilize the Digitally Inclusive Financial Index (DII) from Peking University to quantify the power of technology, specifically using the depth or width statistic. The correlation remains significant, suggesting that for every unit gain in digital Transformation independence, there is an equivalent rise of 0.0041 units in corporate labor recruiting.

Column (E): We do a regression analysis again, removing data that may have been influenced by the 2010 European financial crisis and the 2021 COVID-19 pandemic. The coefficient of digital transformation independence is positively and significantly correlated with a value of 0.0998 ($p < 0.01$).

Column (F): We evaluate the deterministic impact of the "Broadband connectivity China" strategy using a difference-in-differences (DID) approach. The control and treatment groups are determined by the cities' involvement in the strategy and the duration of its execution. The Treat*Post coefficient, which is positive and significant, implies that digital inclusion had a favorable impact on workforce recruitment following the implementation of the strategy.

4.5. Analyse for heterogeneity

Many variables, such as ownership by firms, industry competitiveness, and the local economic climate, could affect the impact of digital transformation on workforce engagement. In this discussion, we explore the variation in the effect of digital transformation on workforce engagement under the scenarios indicated before.

The regression results are reported in Table 5. Columns (A) and (B) analyze the extent of the firm's market dominance using the Herfindahl-Hirschman Index (HHI): an HHI of 0.2 or above indicates a market with an oligopoly organization, whereas a value below 0.1 indicates an antagonistic market framework. The results indicate that the predicted coefficient of digital transformation is positively significant in both competing (0.0820, $p < 0.05$) and oligopolistic (0.1255, $p < 0.1$) environments. Therefore, companies with an advantage are more likely to invest in improving their workforce to further strengthen their edge over rivals.

The regression outcomes for the heterogeneity testing are presented in Table 5.

Variable	(A)	(B)	(C)	(D)	(E)	(F)
	H-HHI	L-HHI	State	N-State	H-Market	L-Market
DT	0.1378* (1.934)	0.0845** (2.456)	0.0599 (0.945)	0.0974*** (2.467)	0.0832** (2.678)	0.5691* (1.987)
SIZES	0.7056*** (20.456)	0.7123*** (32.567)	0.6547*** (11.345)	0.6879*** (36.985)	0.7261*** (36.345)	0.6361*** (14.678)
R&E	-0.3709*** (-1.908)	-0.1567 (-1.897)	-0.2907 (-1.567)	-0.2345*** (-2.978)	-0.3098*** (-2.521)	-0.1598 (-0.607)
AGED	0.2956*** (2.987)	0.1332 (1.786)	0.4429 (1.045)	0.2120** (2.786)	0.1495** (2.657)	0.5091** (2.345)
RD&I	0.0095** (2.876)	0.0059** (2.123)	0.0045 (0.764)	0.0049** (2.789)	0.0056** (2.567)	0.0065 (1.756)
FS	-0.0490 (-0.567)	0.0670 (0.954)	0.0346 (0.256)	0.0785 (0.987)	-0.0134 (-0.198)	0.0786 (0.456)
FA	-0.1721*** (-5.234)	-0.2767*** (-9.345)	-0.1722*** (-3.456)	-0.3744*** (-10.123)	-1.0779*** (-10.678)	-2.0698*** (-4.256)
TobinQ	0.0362*** (2.701)	0.0123* (1.879)	-0.0789*** (-3.372)	0.0245*** (3.461)	0.0234*** (3.131)	0.0056 (0.343)
Constant Term	-9.1228*** (-11.430)	-9.5573*** (-18.356)	-8.5433*** (-3.965)	-9.5405*** (-22.491)	-9.8933*** (-21.123)	-8.4531*** (-10.128)

Variable	(A)	(B)	(C)	(D)	(E)	(F)
	H-HHI	L-HHI	State	N-State	H-Market	L-Market
Firm Effect	handled	handled	handled	handled	handled	handled
Time Effect	handled	handled	handled	handled	handled	handled
Regional Effect	handled	handled	handled	handled	handled	handled
Industry Effect	handled	handled	handled	handled	handled	handled
N	3498	6788	876	8864	8456	1478
R^2	0.9222	0.9345	0.9678	0.9234	0.9156	0.9367
adj. R^2	0.8999	0.9234	0.9532	0.9102	0.9089	0.9245

Note: t-statistic values are in parentheses. * $p < 0.01$, ** $p < 0.05$, and *** $p < 0.10$.

The study distinguishes between government-owned and non-governmental firms (columns C and D). The coefficient of 0.0974, which is both positive and statistically significant, indicates that non-state firms effectively utilize digital transformation to enhance workforce composition. This might be attributed to the more potent motivation of private firms to optimize their processes and enhance productivity, in contrast to government ownership in manufacturing industries.

Columns E and F analyze the influence of a region's business climate on digital transformation. Acknowledging that a high local gross domestic product does not automatically provide an advantageous economy for businesses is crucial. We employed the categories outlined in the "Research Report on China's Provincial Business Environment 2020." Communities that score above the median on the business environment index are categorized as high-market (H-market). In contrast, those with a below-average score are categorized as low-market (L-market).

The findings are captivating. The coefficient of digital independence is positively and significantly correlated with both the H-market (0.0832) and L-market (0.5691). This implies that implementing digital transformation can improve employees, especially among regions with less advantageous economic conditions. Firms operating in these regions may be more motivated to utilize technological innovations to overcome constraints established by the local business landscape.

4.6. Central mechanics

Following that, we employ a mediation approach to examine the fundamental processes by which digital transformation influences the nation's workforce. Table 6 presents the regression findings for various techniques, whereas Table 7 displays the findings for the intervention route test using Bootstrap sampling with 1000 repeats. Table 6 has an equal number of columns for every procedure, as the incremental regression approach was employed to examine its mediation impact. More precisely, we begin by including the correct algorithm as a dependent factor (A column) before proceeding as an independent variable (B column).

Table 6. Regression results for testing underlying mechanisms.

	(A)	(B)	(C)	(D)	(E)	(F)
	opacf	lnHC	FIRM Sales	lnHC	M&E	lnHC
DT	0.0987*** (2.943)	0.1389*** (4.453)	0.0789*** (4.245)	0.0991*** (2.823)	-0.0239*** (-4.954)	0.1234*** (3.876)
SIZES	0.1513*** (11.136)	0.7523*** (44.612)	0.9099*** (84.943)	0.5928*** (22.789)	-0.1292*** (-8.987)	0.6994*** (39.456)
R&E	0.9872*** (9.999)	0.0986 (1.112)	0.1567*** (3.008)	-0.2987*** (-3.976)	-0.1289*** (-12.768)	-0.1645** (-2.234)
AGED	-0.0897* (-2.859)	0.1276** (3.284)	0.1345*** (4.874)	0.1564** (2.983)	-0.0156 (-1.927)	0.1832*** (2.906)
RD&I	-0.0321 (-1.723)	0.1134** (2.564)	-0.0903 (-0.675)	0.0876** (2.671)	0.0025*** (3.654)	0.0048** (2.435)
FC	-0.0456 (-0.932)	-0.0456 (-0.189)	0.2345*** (6.004)	-0.1234 (-0.145)	-0.0987*** (-5.123)	0.0546 (0.897)
FA	-0.2345***	-0.1768***	-0.2654***	-0.0657***	0.0324***	-0.1234***
	(-16.657)	(-13.546)	(-19.678)	(-6.789)	(15.234)	(-12.145)
TobinQ	0.0123 (0.678)	0.0346*** (2.376)	0.0236*** (5.684)	0.0267*** (3.716)	0.0167*** (3.134)	0.0234*** (2.567)
opacf		-0.5520*** (-17.468)				
FIRM Sales				0.1886*** (3.985)		
M&E						0.8987*** (7.234)
Constant Term	5.8876*** (18.234)	-6.8545*** (-18.456)	1.6543*** (6.879)	-9.7896*** (-24.999)	0.6543*** (12.234)	-9.9768*** (-25.345)
Firm Effect	handled	handled	handled	handled	handled	handled

	(A)	(B)	(C)	(D)	(E)	(F)
Time Effect	handled	handled	handled	handled	handled	handled
Regional Effect	handled	handled	handled	handled	handled	handled
Industry Effect	handled	handled	handled	handled	handled	handled
<i>N</i>	9658	9658	9658	9658	9658	9658
<i>R</i> ²	0.8578	0.9346	0.9879	0.9189	0.8960	0.9367
adj. <i>R</i> ²	0.8456	0.9289	0.9775	0.9023	0.8833	0.9234

Note: t-statistic values are in parentheses. **p* < 0.01, ***p* < 0.05, and ****p* < 0.10.

The outcomes of the operation channels test are presented in Table 7.

ITEM	TOTAL EFFECT	BOOT.LLC I	BOOT.ULC I	MEDIATING EFFECT VALUE	DIRECTLY EFFECT	TEST OUTCOMES
Digital Transformation ⇒ Managerial Efficiency ⇒ Workforce Employment	0.0940** *	0.031	0.061	0.0401*** (3.998)	0.1634*** (4.855)	Mediation Effect
Digital Transformation ⇒ Economies Scale ⇒ Workforce Employment	0.0940** *	0.002	0.010	0.0051** (2.435)	0.1976*** (5.799)	Mediation Effect
Digital Transformation ⇒ Total Factor Productivity ⇒ workforce Employment	0.0940** *	-0.312	-0.231	-0.2401*** (-10.103)	0.4378*** (12.956)	Cover Effect

Note: t-statistic values are in parentheses. * $p < 0.01$, ** $p < 0.05$, and *** $p < 0.10$. BOOT.LLCI and BOOT.ULCI denote the lower and upper limits of the 95% interval for Bootstrap sampling, respectively.

The impact of digital Transformation on workforce recruiting seems quite complex and varied. Upon analyzing Table 6, it becomes evident that the use of technology results in a rise in total factor productivity (TFP), as indicated in column A. Consequently, this boost in TFP leads to a parallel rise in the needed labor, as shown in column B. This provides evidence in favor of hypothesis H2c. Likewise, digital Transformation promotes economies of scale (column C), enabling companies to gain cost benefits as they expand, eventually contributing to increased employment (column D). This is consistent with hypothesis H2b.

The findings on management efficiency (H2a) are particularly fascinating. Although digital transformation may seem first to reduce management efficiency (column E), it ultimately results in increased labor recruiting (column F). This implies an arrangement that is more intricate and intricate. Digitalization may first disturb organizational structures, but it ultimately leads to workforce expansion via many means.

Table 7 provides additional support for the existence of these mediated effects. The bootstrapping sample provides evidence that management effectiveness, economies of scale, and total factor productivity all have a significant impact, as indicated by a 95% confidence interval that does not include 0. Digital independence has a negligible impact of 0.0940 on workforce recruitment. An analysis of the direct and indirect impacts uncovers a captivating interaction:

Management efficiency: The net impact of digitalization on workforce recruiting is positive, with the indirect effect (0.1634) being more significant than the direct effect (0.0401). This indicates that although digitalization may immediately disturb some management procedures, it does improve workforce recruitment in the long term.

Economies of scale may be confirmed as a significant mediation strategy based on the considerable positive indirect effect (0.1976) compared to the lower direct effect (0.0051).

The negative direct effect, with a magnitude of -0.2401, is offset by a more significant positive indirect effect, with a magnitude of 0.4378. This implies a more intricate and subtle function for Total Factor Productivity (TFP). Digitalization may initially have a detrimental influence on total factor productivity (TFP), but this is ultimately surpassed by the beneficial impacts resulting from other variables.

Conclusion

The research elucidates the complex correlation between digital transformation and the recruitment of manufacturing-based workforce in China. Economists and policymakers can utilize the data we obtained from research using a panel fixed-effects model, which analyzed 1157 A-share-listed enterprises from 2010 to 2022. Job advancement is influenced by digital transformation. We have shown that when individuals are given digital empowerment, it has a notable and statistically significant impact on employment rates, increasing them by 9.36%. This finding contradicts previous research that examined a broader range of Chinese firms, suggesting that it may be influenced by specific characteristics related to certain sectors. There appears to have been a link between the increase in labor demand and manufacturing firms' technological innovations to enhance productivity and expand capabilities. Based on these findings, digitization can enhance productivity in some industries, particularly those undergoing swift technological advancements.

The impact of digital transformation on recruitment varies between companies due to disparities in ownership, the amount of competition in the industry, and the economy in general. The positive impact is most noticeable for companies functioning in oligopolistic markets, free from government regulation, or in suboptimal firms. Private firms may have more freedom to explore new digital advances to optimize labor utilization. As the profitability of oligopolistic firms increases, they are more inclined to invest in technological advances and expand their workforce. The increased need for personnel might be attributed to companies' strategic application of digitalization in challenging sectors to surpass limitations and enhance operational efficiency. When analyzing the impact of digital transformation on employment sectors, it is essential to consider the industry foundation and company characteristics, as demonstrated by the following results.

With prior research, we discovered that digital transformation promotes a shift toward a higher proficiency-level workforce. Professionals with expertise in creativity, management, and other diverse areas are highly sought after due to the transformative impact of digital technology and processes on corporate operations. This trend highlights the significance of education and training programs in equipping current and future workers with the necessary skills to thrive in a digitalized manufacturing environment. Regulators are essential in promoting upskilling initiatives to address potential skill shortages and facilitate the workforce transition.

The positive effects of digital transformation on workforce recruiting are moderated by enhanced management efficiency and economies of scale. Utilizing digital technology may improve administrative processes and ultimately lead to a larger workforce by simplifying processes, enhancing decision-making, and maximizing resource utilization. Digitization enables companies to achieve economies of scale, reducing manufacturing costs per unit of item or service. By reducing expenses, firms could allocate additional funds toward expanding their operations and hiring more staff. Understanding the mediator effects is crucial for comprehending how digital transformation influences labor demand.

This article demonstrates that digital transformation can enhance employment opportunities in the industrial sector, particularly for those possessing advanced degrees. The specific nature of the repercussions is determined by the firm's characteristics and the marketplace's conditions. Based on these findings, economists and political stakeholders may develop strategies that optimize the beneficial impacts of digitalization on workers while mitigating its adverse implications. Future research may focus on the potential automation and job displacement in specific industries alongside the lasting impact of modernization on employment prospects.

Discussion

Our study analyses the intricate relationship between technological transformation and the human asset environment in China's manufacturing industries. We demonstrate that digital autonomy enhances managerial efficiency and amplifies the advantages of scaling up. Aligned with other studies on the positive impacts of digitalization on companies and sectors, this leads to a more skilled and proficient workforce. However, our investigation goes beyond simply confirming previous trends. The potential for digital transformation to drive the progress of employees is a fascinating aspect of our research. If technological innovations enhance governance and financial efficiency, firms may allocate more funds toward educational possibilities for their workers. Professionals may acquire the necessary skills to thrive in the contemporary digital landscape by upskilling and alleviating concerns about automation replacing their work.

Our insights indicate that the impact of digital transformation on the workforce might differ. In the future, scholars may examine the impact of digitalization on workforce requirements, taking into account factors such as business size, manufacturing specialism, and geography. Our research elucidates the complex correlation between digital transformation and the manufacturing workforce in China. Digitalization in the industry has both benefits and drawbacks. On the positive side, it may enhance managerial efficiency, result in economies of scale, and foster human capital growth. Increased research into the intricacies of this relationship can be advantageous for companies and legislators who aim to formulate successful strategies for the future of digitalized manufacturing.

Limitations

Regarding the deficient proportion of missing information in our stated company reports (about 2%), we have decided to remove it. In order to rectify any missing data and guarantee the reliability of the findings, further studies might explore other approaches, such as restoring. To conduct a more comprehensive investigation, researchers might expand the range of data to include manufacturing firms in Asia or worldwide. Our study overlooked important nuances in quantifying digital transformation since it relied on existent indicators of the concept. The research identified total factor productivity, scale economies, and management efficiency as the primary mediating factors. However, there are additional components that could act as mediators. Future studies explore the relationship between digital transformation and workforce employment by examining the impact of supply chain management, operational strategies, financial tactics, and governance frameworks. Whether developed internally or by other entities, these apps have the potential to enhance the influence of digital transformation and produce fresh employment opportunities. Future studies in this field provide insight into the growth of the digital environments in manufacturing firms.

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